The Quality of Private Monitoring in European Banking: Completing the Picture

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The Quality of Private Monitoring in European Banking: Completing the Picture

Abstract: The philosophy behind the debt market discipline approach to banking regulation presumes that the pricing of bank debt securities, if accurate, conveys reliable signals to supervisors. In this paper, we take a critical look at the feasibility of such an approach by exploring empirically the possibility that markets may price *differently* the risk profile of bank issuers along the empirical distribution of credit spread. The paper proposes a quantile regression framework to draw novel inferences about the functioning of market discipline and the quality of private monitoring in European banking and provides a more comprehensive picture of the distribution of spreads conditional on its main explanatory factors. We find that the spread-risk relationship is systematically *steeper* and *more significant* at the "right-tail" of the conditional distribution of credit spread, which suggests that the market is somewhat tougher with "high-risk" banks.

Keywords: Banking regulation and supervision; Market discipline; Subordinated debt; Private monitoring; Credit spreads; Quantile regression

JEL classification: G21; G28

1. Introduction

The idea to integrate market discipline into the prudential regulation of banks is not entirely new. Complying with a requirement of the American Congress, the FDIC[1] conducted a first study on the various reform options likely to strengthen market discipline in banking in April 1983. From then on, market discipline has drawn increasing attention among researchers and policy makers.[2]

In the US, the financial modernization Gramm–Leach–Bliley Act enacted in November 1999 required a report to Congress on the feasibility of the proposal to reinforce market discipline through a mandatory policy forcing the largest banks to issue subordinated debt (Subordinated Debt Policy or SDP).[3] The conclusion of this report, conducted by the Federal Reserve and Treasury Department, was that additional evidence must be gathered before they can support a request for legislative authority to implement a mandatory SDP in the US (see BGFRS&TD, 2000). The report calls for continued research on this topic and encourages the use of market information derived from *voluntary* sub-debt issues in banking supervision. "Market discipline" is also one of the three pillars on which the Basel II capital adequacy accord is founded.[4] However, the third pillar of Basel II is exclusively focused on the information disclosure process and remains silent about the ways market discipline might strengthen bank regulation and supervision. The Basel Committee's official response to the subprime financial crisis, crystalized in a new Basel III capital accord, does not add much to the partial approach to market discipline in Basel II.

The recent financial crisis has revealed, at least from a macro-prudential perspective, severe deficiencies in both the supervisory *and* market discipline mechanisms (see Financial Services Authority, 2009, for a critical view on the functioning of market discipline and Acharya and Richardson, 2009, for an extended discussion of regulatory failures). However, the vast majority of post-crisis reform proposals

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[1] Federal Deposit Insurance Corporation (FDIC) is the government body charged with the deposit insurance in the United States.
[2] Bliss (2001) and Hamalainen et al. (2005) provide comprehensive analyses of the theory underlying market discipline in banking and highlight the multi-dimensional structure of the phenomenon.
[3] See for instance Calomiris (1999, 2006). For an excellent survey of the various sub-debt proposals, the reader can refer to BGFRS (1999, Table 1, pp. 6–12), BGFRS&TD (2000, Appendix A, pp. 58–65) or Evanoff and Wall (2000, p. 67 *et passim*).
[4] The other two pillars are: (I) the bank capital regulation and (II) the supervision process. Rochet (2004) examines the articulation between the three pillars of Basel II in a general continuous-time stochastic model. Yet, when he the author formalizes the third pillar, he focuses on a Sub-Debt type Policy and not on public disclosure requirements as the Basel Committee does.

agree that any future changes to the regulatory framework should be made without destroying private incentives or damaging market discipline.

The functioning of debt market discipline in banking supposes the effectiveness of two main transmission channels (see BGFRS, 1999). Firstly, a *direct* channel could be activated *via* the cost of issuing debt, which theoretically should be sensitive to a change in the bank risk profile. Thus, the appropriate pricing of bank risk in the bond market could dissuade (*ex-ante*) banking organizations from taking excessive risks. Secondly, an *indirect* channel can be effective as long as the supervisor and other market participants observe the market prices or spreads and infer reliable signals concerning the default probabilities of issuing banks. For example, the supervisor may use this alternative source of information (along with other public and/or private sources) when triggering Prompt Corrective Actions, setting up risk-adjusted deposits insurance premia or allocating scarce resources.

For market discipline to be effective, a necessary (albeit non-sufficient) condition is that market prices or spreads be sensitive to bank risk. To assess the disciplinary potential of the bank debt market, some previous papers, including *inter alia* Avery et al. (1988), Gorton and Santomero (1990), Flannery and Sorescu (1996), Morgan and Stiroh (2001), Jagtiani et al. (2002), Covitz and Harrison (2004), Covitz et al. (2004), Krishnan et al. (2005, 2006), Evanoff et al. (2008), Santos (2009) attempted to determine the extent to which (*primary* and *secondary* market) spreads accurately reflect issuers' financial conditions. These studies generally confirm that the private monitoring is effective in the US and other developed bank debt markets, at least under *normal* banking conditions: market prices reflect quite well past and contemporaneous conditions of issuing banks and this information is not redundant with regard to that possessed by the supervisor.[5]

The literature has moved on recently to other relevant topics and attempted to address complementary questions, namely: "*Do yields reflect risk in time to act sooner?*"; and "*Is the market able to influence bank soundness and managers' actions?*" A number of recent papers explore these areas, with mixed results (see DeYoung et al., 2001; Evanoff and Wall, 2001, 2002; Gropp et al., 2006; Krainer and Lopez,

[5] See BGFRS (1999), Flannery (1998, 2001), Evanoff and Wall (2000), and Flannery and Nikolova (2004) for comprehensive surveys of the US evidence. The empirical literature on the effectiveness of market discipline in other countries is quite thin, compared with the US evidence (see e.g. Bruni and Paternò, 1995, Sironi, 2003, Gropp and Richards, 2001, Gropp and Vesala, 2004, Gropp et al., 2006). Coffinet et al. (2009) and Hamalainen et al. (2011) are among the very few papers that investigate this issue under *stressful* market conditions.

2004; Coffinet et al., 2009, for the underlying timeliness question;[6] Bliss and Flannery, 2002; Cihak et al., 2009, for the influencing issue).

In this paper, we contribute to the extant literature by taking a critical look at the feasibility of the market discipline approach to banking supervision. Particularly, we explore empirically the possibility that debt markets may be "correct" sometimes and "wrong" at others; or, to put it another way: markets may price correctly the risk profile of *some* banks, but may fail to price the risk of a specific set of banks, located at the right-tail of the distribution of the credit spread variable (i.e. "high-risk" banks). To put this idea into perspective and for illustrative purposes only, we use an extensive dataset of spreads, ratings, and accounting measures of bank risk for a sample of large European banks in order to test empirically whether there are systematic differences in the determinants of "low-risk" and "high-risk" banks, as perceived by the market.

The answer to this research question has broad implications and is highly relevant in the public policy arena. Indeed, as one of the main objectives of supervision is to correctly identify the worst 5 or 10% of banks, it is important to draw appropriate inferences about the risk sensitivity of credit spreads at the "right-tail" of the distribution. Given the empirical heterogeneity of the data and the skewed distribution of the credit spread variable, an appropriate modeling choice is to use the quantile regression (QR) framework proposed by Koenker and Bassett (1978) and Koenker (2005) instead of classical ordinary least squares (OLS) estimations. Indeed, this empirical heterogeneity may be masked when using standard empirical techniques. The main contribution of the paper is to use a quantile regression framework to draw novel inferences about the functioning of market discipline and the quality of private monitoring in European banking by providing a more comprehensive picture of the distribution of spreads conditional on its main explanatory factors.[7]

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[6] These studies generally compare the ability of various competing indicators (stock and bond market signals, accounting information) to predict changes in external agencies ratings / supervisory ratings or actual events of financial distress.

[7] To our knowledge, this empirical approach is novel to the market discipline literature. However, some recent papers use the QR framework to study other relevant topics in banking regulation. For instance, Adrian and Brunnermeier (2009) use the same approach to construct an interesting measure of risk spillovers (CoVaR) and emphasize the attractiveness of quantile regressions. Schaeck (2008) also use a QR approach to illustrate that bank failure resolution costs are not homogenously driven by the same factors across quantiles.

Basically, we find that the link between market prices and risk proxies varies considerably along the conditional distribution of credit spread, both in terms of statistical significance and economic magnitude. More importantly, the spread-risk relationship is systematically *steeper* and *more significant* at the right tail of the conditional distribution of credit spread. These findings suggest that the market is somewhat tougher with “high-risk” banks, a novel result that may not be captured using standard conditional mean-focused estimations commonly used in the market discipline literature.

The rest of the paper is organized as follows. Section 2 describes the data sources and sample construction, while Section 3 presents the research methodology based on quantile regressions. The main results concerning the spreads sensitivity to various proxies of bank risk across quantiles, as well as the robustness checks, are presented in Section 4. Finally, Section 5 concludes.

2. Data sources and sample construction

To provide a comprehensive picture of the quality of private monitoring in the European secondary bank debt market, we take a fresh look at the relationship between the credit spread and the various measures of bank risk. For illustrative purposes only, we build a dataset containing fundamental risk measures, balance-sheet variables, bank ratings, and market indicators extracted over an eight-year pre-crisis period (1995-2002) from two main sources, *BankScope* and *Datastream Thomson Financial*.[8]

We began by identifying from *Datastream* all the issues of fixed-income securities “alive” at the end of 2002, made by the largest European banks. Detailed information about issue date, redemption date, amount issued, coupon, amortization features, guarantees, optional features, etc. were collected for each of these issues. Following the previous literature, we selected one representative security for each banking organization.[9] To be included in the final sample, the selected issues had to satisfy several

[8] The dataset used in the current version of the paper has limited relevance for our main research question because the variability of market prices and spreads, our dependent variable, is limited during tranquil periods (the LTCM collapse and the Russian moratorium in 1998 are notable exceptions, however). We are updating and extending our dataset in order to investigate the relevance of our intuition on a dataset including large US banks during the subprime financial crisis. As noted by Gilchrist et al. (2010), spread levels for financial firms climbed from 100 bps, before the crisis, to more than 900 bps around the Lehman collapse and spread volatility was off the charts in 2008. The updated version will soon be available.

[9] In the next version of the paper, we construct a *weighted composite spread* for each issuer from a series of bonds that are the most traded /liquid in the market.

criteria: (1) publicly traded in a secondary market; (2) no specific option features (put, call, convertibility, etc.) attached to the issues; (3) fixed coupon rate; (4) *in fine* amortization schedule.

Selecting only “plain vanilla” (i.e. common) fixed-rate bonds is justified by two distinct reasons (see also Jagtiani et al., 2002). First, the selected issues are rather homogeneous and consequently more comparable according to credit risk related factors. Second, we eliminate the additional noise specific to the hypotheses backing the option-adjusted spread calculations. Such models were estimated *inter alia* by Avery et al. (1988) and Flannery and Sorescu (1996).

If several issues made by the same bank fulfilled our eligibility criteria, we preferred those (*i*) that were made before 1995 (to have at least eight years of data), (*ii*) whose amount was the largest one (to reduce the size of liquidity premium) and (*iii*) that were subordinated. For the 70 selected issues, 32 being subordinated, we collected the secondary market prices on December 31st over an eight-year period.

Once the issuers were identified, we added to our initial dataset their credit ratings and other accounting items (consolidated figures) reported in *BankScope*. Because not all banks had outstanding debt securities at the end of each year of the analyzed period, we assembled an unbalanced sample including a maximum of 521 observations (bank-year). It is worth noting that our final sample is comparable in size to those used by Flannery and Sorescu (1996, 83 issuers) and Jagtiani et al. (2002, 58 issuers).

3. Research methodology, model specification, and definition of the main variables

The most appropriate econometric tool to answer our main research question is the quantile regression (QR) framework described in Koenker and Bassett (1978), Koenker and Hallock (2001), and Koenker (2005). QR constitutes an interesting extension of the standard conditional-mean focused OLS estimation. The idea behind the QR approach is to estimate a full set of empirical models for different conditional quantile functions. To briefly recall the basic principles, the p^{th} quantile or percentile of a random variable Y characterized by the distribution function $F(y) = P(Y \leq y)$ is defined as:

$$Q^{(p)} = \inf\left[y : F(y) \geq p\right] \quad (1)$$

where p moves along the]0; 1[interval. The quantile function provides a comprehensive characterization of Y, in a similar manner as the distribution function: $Q^{(.10)}$ defines the first decile, $Q^{(.25)}$ is the first quartile, $Q^{(.50)}$ the median and so on. Assuming a linear relationship between the p^{th} quantile of the conditional distribution of the dependent variable of interest y_i and a vector of $k \times 1$ independent variables x_i, the conditional quantile regression model in its general form may be written as:

$$y_i = x_i'\beta^{(p)} + \varepsilon_i^{(p)}\,,\ i = \overline{1,n} \tag{2}$$

where n is the number of observations; $\varepsilon_i^{(p)}$ is the error term; and $\beta_k^{(p)}$ reflects the marginal change in the dependent variable due to a unit change in the k^{th} regressor conditional on being on p^{th} quantile. The conditional p^{th} quantile is determined by the quantile-specific parameters $\beta_k^{(p)}$ and a specific value of the covariates x_i:

$$Q^{(p)}(y_i | x_i) = x_i'\beta^{(p)} \tag{3}$$

It is assumed that the error term satisfied the usual quantile restriction, $Q^{(p)}(\varepsilon_i^{(p)} | x_i) = 0$. By letting the value of p vary from 0 to 1, we may trace the entire distribution of y conditional on x. So, for any $p \in]0;1[$ the parameter vector $\beta^{(p)}$ can be estimated by solving the following optimization problem using linear programming techniques (simplex iterations):

$$\hat{\beta}^{(p)} = \arg\min_{\beta \in \Re^k} \frac{1}{n} \sum_{i=1}^{n} \rho^{(p)}\left(y_i - x_i'\beta^{(p)}\right) \tag{4}$$

where $\rho^{(p)}$ is the so-called *check function*, naturally defined as

$$\rho^{(p)}(\varepsilon_i^{(p)}) = \begin{cases} p\varepsilon_i^{(p)} & if\ \varepsilon_i^{(p)} \geq 0 \\ (p-1)\varepsilon_i^{(p)} & if\ \varepsilon_i^{(p)} < 0 \end{cases} \tag{5}$$

We apply the general QR framework described in this section to study the risk sensitivity of credit spread depending on whether we are interested in a specific part (left tail / low risk *vs*. right tail / high risk) of the distribution of the dependent variable. The empirical framework of our analysis is based on the general quantile regression model linking the yield spread to various measures of bank risk:

$$\text{SPREAD}_{it} = f^{(p)}(X_{it}, Y_{it}, Z_{it}) + \varepsilon_{it}^{(p)} \tag{6}$$

SPREAD_{it} = the difference between the bank bond yield to maturity and the yield of a corresponding currency Treasury security;

X_{it} = market measures of bank risk;

Y_{it} = accounting measures of bank risk;

Z_{it} = other control variables likely to affect SPREAD_{it}.

The linear form of the function $f^{(p)}(\cdot,\cdot,\cdot)$ can be viewed as an approximation, more or less accurate, of the SPREAD/risk relationship:[10]

$$Q^{(p)}(\mathrm{SPREAD}_{it} | X_{it}, Y_{it}, Z_{it}) = \alpha^{(p)} + \gamma_t^{(p)} + \beta^{(p)} X_{it} + \sum_{k=1}^{K} \xi_k^{(p)} Y_{kit} + \sum_{j=1}^{J} \psi_j^{(p)} Z_{jit} \qquad (7)$$

We estimate the coefficients of independent variables depicted in equation (7) at several representative quantiles $p \in \{.05;.10;.25;.50;.75;.90;.95\}$ and using a common set of independent variables. Standard errors are estimated using the bootstrap method based on 1,000 replications. For the sake of comparability, we also estimated standard conditional-mean regressions (both a pooled specification and an OLS model including bank fixed effects).

The variables of interest are defined as follows. The dependent variable is computed using a method similar to that of actuarial spread, which is the common reference among market professionals. The construction of this type of spread presupposes the choice of a benchmark Treasury security denominated in the same currency and having a maturity or duration similar to that of the risky bond. When there is no benchmark of the same maturity, most authors (Jagtiani et al., 2002; Sironi, 2003, *inter alia*) use linear interpolations. In contrast to these studies, we use an alternative measure of actuarial spread, which integrates all the information contained in the risk-free yield curve. Initially, we built the risk-free term structure from a panel of Treasury securities (like OAT and BTAN for France, BUNDS and BOBL for Germany, etc.).[11] Then, we calculated the yields on each bank debt issue using the market gross prices

[10] Note however, that the intercept and slope parameters may well vary with the quantile. So, the QR framework is robust to nonlinearities in the SPREAD/risk relationship. For instance, the samples constructed by Avery et al. (1988), Gorton and Santomero (1990), and Flannery and Sorescu (1996) exhibit a (quasi-)linear relationship between SPREAD and bank assets risk. However, Jagtiani et al. (2002) show that, in the case of undercapitalized banks, SPREAD increases faster with risk.

[11] The risk-free yield curves were estimated for seven different sovereign issuers (*viz*. France, Germany, Italy, the Netherlands, Switzerland, the United Kingdom, and the United States) according to the currency in which the bank

(including the accrued interest) collected at the end of each year of the analyzed period.[12,13] The benchmark yield is estimated by substituting the bank debt maturity in the cubic equation that describes the risk-free yield curve of the corresponding sovereign issuer. Finally, the difference between the two yields defines our dependent variable $SPREAD_{it}$ (expressed in percentage) for each bank issuer at the end of each year of the analyzed period.

The data concerning the SPREAD variable are presented in Table 1. The level of spreads, relatively low (0.6% on average) at the beginning of the analyzed period, has increased since 1998 (at about 1% on average). The fourth column of the same table exhibits similar patterns for the SPREAD volatility. The standard deviation of SPREAD had gradually increased from 0.35% in 1995 to more than 1% in 2002. The interquartile range (Q_3–Q_1), a variability measure less sensitive to extreme values, had a similar evolution over the considered period. The highest spreads, recorded at the end of 1998, were caused by the Russian default of August 1998, which seriously impaired the pricing in the bank debt market both in the United States and Europe (see Hancock and Kwast, 2001; Sironi, 2001). The major quantiles of the credit spread variable are illustrated graphically in Figure 1. The plot is very similar to that of the empirical cumulative distribution function (c.d.f.) except that the axes are reversed. The distribution is reasonably symmetric for $p \in [.10;.90]$ although it contains some extreme observations at the right tail.

{Table 1 about here}

{Figure 1 about here}

The distribution of SPREAD by country, depicted in Table 2 (columns 3&4), reveals some interesting aspects. Firstly, German, Austrian and French banks have lower spreads (0.59%, 0.59%, and 0.75% respectively) than the European average (0.87%). This stylized fact could be explained by, among other

debt issue was denominated. Estimation details for best fit calculations of benchmark yield curves are presented in Appendix 1.

[12] The market price is the latest price obtained from the market, quoted either as a clean or gross price, depending on local market practices. For some markets, this is the current real-time price; for others, it is last night's closing price. It is always a mid-price. Certain data providers (e.g. *Bloomberg*) report "indicative" quotes or "predicted" (matrix/BGN) prices, which are not necessarily based on actual trades. However, private correspondences with the team *Datastream* (London) confirmed us that all the prices used in our study always correspond to actual trades.

[13] The accrued interest is calculated according to conventions governing each market. The yields calculations depend on the practices specific to each market, e.g. semi-annually in the US Treasury market and annually in the Eurobonds market.

things, the larger shares held by the public-sector banks in these countries over the analyzed period. Secondly, the UK, Spanish, Italian, and Swedish bank bonds exhibit above European average spreads.[14]

{Table 2 about here}

Among the control variables, the issue size is relatively large (US$ 260.17 million, on average), while the average maturity is about 11 years. The vast majority of the issues are international (72%, including Eurobonds). As *Datastream* supplies information concerning the subordination status only for the international issues, we could identify no more than 32 subordinated bonds. Finally, in our sample, about 20% of bank issuers belong to the public sector, benefit from explicit governmental guarantees, or are assigned with a Fitch–IBCA Support rating equal to 1. Most of these special institutions are located in Germany, Austria, and France.

We use several proxies for bank risk often employed in the literature. The market measures of bank risk (X_{it}) are the traditional credit ratings and the financial strength ratings assigned exclusively to banks. Because no data on specific bank debt issue ratings was available, we used the issuer ratings attributed by the most active international agencies (Standard and Poor's, Moody's, and Fitch–IBCA) instead. The three agencies use relatively similar scales and criteria, and assign rather comparable ratings. The Pearson correlation coefficients between the various credit ratings are all positive and strongly significant. Furthermore, differences higher than one notch are observed only in one of ten cases when two rating agencies rated the same issuer. The ratings are converted to cardinal values according to the scale presented in Appendix 2. A lower cardinal value corresponds to a higher credit quality.

Finally, the SP-M-FI$_{it}$ variable is the average of ratings assigned by the three agencies to bank i at the end of year t. The time evolution of this variable, described in Table 1, is less marked than the evolution of SPREAD, reflecting the vision "through the cycle" of rating agencies and their lethargic adjustment behavior. The distribution by country (Table 2) reveals that German banks are better rated (2.71 or AA+/AA1) than the European average (3.81 or AA–/AA3). Moreover, the negative relationship between SPREAD and SP-M-FI is consistent with financial theory (see Table 3, panel A): a lower quality rating

[14] Sironi (2003) also finds that German/UK banks pay spreads significantly lower/higher on the *primary* market with regard to their European competitors.

corresponds on average to a relatively higher spread, in spite of the fact that interquartile intervals are not always disjoint.

{Table 3 about here}

Although the traditional credit ratings are synthetic market measures of bank solvency, they do not necessarily reflect the genuine risk profile of issuing banks. In the presence of *de jure* (for public-sector banks) or *de facto* (for "too-big-to-fail" banks) governmental guarantees, the capacity of an entity to honor its debt service could be excellent even if its intrinsic financial conditions are poor. The rating agencies have soon recognized this problem and proposed new ratings, focused on the intrinsic safety and soundness of banks, which exclude certain external credit risks and credit support elements addressed by traditional ratings. These ratings can be considered as an objective evaluation of the likelihood that a bank needs to seek an outside support, either from state authorities or its shareholders.

Moody's Bank Financial Strengths (MBFS) and Fitch–IBCA Individual (FII) ratings, both specific to banks, are two examples of such ratings. The Pearson correlation coefficient between the two ratings is about 0.76, whereas differences higher than one notch are recorded more often (in 24% of common ratings) than in the case of traditional ratings. The MBFS-FII continuous variable, representing the average of the two ratings, was computed as in the previous case (i.e. of the SP-M-FI variable).

All banks included in our sample are classified as investment grade (minimum BBB+/Baa1) according to the traditional ratings, but once the influence of the safety net is eliminated (by considering the MBFS-FII ratings), this assignment is no longer valid. Table 3 (panel B) proves the existence of a certain number of D/E+ rated banks that have very poor financial conditions. According to Table 2 (columns 5&6), the largest differences between traditional and financial strength ratings are observed in the case of German and Austrian banks. These simple descriptive statistics suggest that the safety net protecting banking systems in these countries are relatively more generous than those adopted in the UK or Switzerland for example.[15]

To explain better the SPREAD variability, we used several accounting measures of bank risk (Y_{kit}), usually employed in the literature, and a whole series of control variables (Z_{jit}) (see Table 4 for a brief description of the main explanatory variables).

[15] For Swiss and UK banks, the traditional and MBFS-FII ratings are well aligned.

{Table 4 about here}

The accounting variables are observed at the end of each year of the analyzed period, for each bank issuer. Yet, the financial statements are publicly disclosed several weeks after the end of the year. So, on the last day of the year (December 31st), the various bank-specific measures of the risk profile (Y_{kit}) are not yet publicly released; they may only be known with some "error." By not taking into account the fact that accounting data are reported with a lag, our tests should be biased against finding a significant relationship between the various financial ratios and spreads. To deal with this problem of measurement errors in variables, we compute the SPREAD variable using the market prices observed on January 31st of each following year, which post-date the release of financial statements. This approach is suggested by Flannery and Sorescu (1996), and Jagtiani et al. (2002). Specifically, the main analysis will be done using end-of-January spreads and credit rating data along with year-end accounting data.

4. Is the market tougher with "high-risk" banks?

To address our main research question, we report in Tables 5 & 6 the results of quantile regressions (with bootstrap standard errors) when banking risk is proxied by the traditional credit ratings and financial strength ratings. For the sake of comparability, we also report in the same tables the results from the estimated standard conditional-mean regressions, with heteroskedasticity-robust standard errors: a pooled specification and an OLS model including bank fixed effects (FE). It is worth noting that the two OLS specifications are not directly comparable since the FE model cannot include time-invariant control variables (e.g. country dummies; amount issued; maturity; subordination status).

{Table 5 about here}

{Table 6 about here}

The OLS coefficient estimates of the rating variables (SP-M-FI and MBFS-FII) are strongly significant (at the 1% level) and have a positive sign, as expected: the lower the rating, the higher the yield spread required by investors. On average, a one-notch downgrade of the traditional (financial strength) rating implies an increase of the spread by 6.4 bps (4.7 bps).[16] However, as it is well known, the

[16] The estimated elasticity of spread to the traditional rating is comparable with that reported by Jagtiani et al. (2002, Table 3, p. 572) on US data, between 1992 and 1997, i.e. of 6.1.

OLS estimated coefficients only characterize the mean tendency of the spread distribution and do not capture the possibility that the risk sensitivity may be *different* for high- and low-risk banks. The QR parameter estimates allows comparing how some quantiles of the credit spread may be more or less affected by certain covariates than other quantiles. The changes in the size and significance of the QR coefficients reflect some interesting patterns: the impact of our basic risk proxies vary considerably along the conditional distribution of spread, both in terms of statistical significance and economic magnitude. Particularly, the risk sensitivity of credit spreads is *stronger* and *more statistically significant* in the upper tail of the distribution: while the lower (5^{th} quantile) elasticity is .027 (non significant) and .027 (significant at the 5% level) for traditional and financial strength ratings, respectively, the strongest impact rate (95^{th} quantile) is .210 and .174, respectively, both statistically significant at the 1% level. Notice also that the goodness of fit of QRs, measured by the pseudo R-squared defined as 1 – [*sum of the weighted deviations about estimated quantile / sum of weighted deviations about raw quantile*], is higher when $p > .75$, indicating that credit spreads are better linked to the main explanatory factors *at the upper tail*.

An attractive way to illustrate this finding is through a graphical representation of the coefficients of interest and their respective confidence bands. Figures 2 & 3 present for each of the rating coefficient a full set of distinct QR estimates for p ranging from .05 to .95 as solid gray curves. The horizontal axis represents the quantile p scale and the vertical axis indicates the marginal effect of each of the covariates. The shaded area depicts a 95% confidence interval for the QR estimates and the dashed line in each figure shows the OLS estimate of the conditional mean effect, which do not vary with the quantile p. Both figures indicate that the impact of rating variables on spread is much stronger at upper quantiles. Notice that the QR estimates lie outside the confidence bands of the OLS regression, indicating significant departures from the mean effect at the right tail of the distribution.

{Figure 2 about here}

{Figure 3 about here}

The bootstrap procedure is adapted to estimate the simultaneous or joint variance-covariance matrix corresponding to the parameter estimates $\hat{\beta}^{(p)}$ across different specified values of p, allowing us to conduct Wald tests for the equality of the estimated coefficients across quantiles. The last three columns of Tables 5 & 6 report the *F*-statistics and the associated significance levels for the null hypothesis of homogeneous coefficients: (i) equality between 1st and 3rd quartiles; (ii) equality of coefficients at the median and at the tails; and (iii) equality across tails between 5th and 95th quantiles. The tests generally confirm the inference from the visual inspection: the null hypothesis of homogenous SP-M-FI coefficients is soundly rejected. The same hypothesis is rejected in only one instance at conventional significance levels when risk is proxied by the financial strength rating MBFS-FII, namely when we test the equality between 1st and 3rd quartiles.

The effects of the other control variables are as expected. The issue size (ln(AISD)) has a negative and significant coefficient: the amount issued is often associated to indirect measures of the secondary market liquidity. The idea is that smaller issues are likely to be more easily absorbed in investors' portfolios, thus reducing market liquidity (see BGFRS, 1999; Basel Committee, 2003). The maturity (MATU) of the issue has a positive coefficient indicating that the default probability is an increasing function of the investment horizon (the effect is stronger at the lower tail). The coefficient of the *Split* variable is positive suggesting that bank issuers which are rated differently by the two major US agencies have higher spreads. We included the *Support* variable into the specification comprising the MBFS-FII ratings in order to control for the conjectural governmental guarantees and bailout policies.[17] The negative coefficient of *Support* reveals that the debt issued by European public-sector banks is traded at spreads that are relatively low with respect to their intrinsic risk profile. The QR estimates for the coefficients of the control variables do not exhibit clear patterns.

The results of OLS and QR estimations of the model including accounting variables are reported in Table 7. To focus on the baseline story of the paper, we will confine our discussion to only a few of the covariates, namely the risk proxies. Generally, the findings in terms of SPREAD sensitivity are less conclusive than those discussed previously.[18] The various variables quantifying the credit risk (*Loan Loss*

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[17] We preferred this specification, because unlike the one including the traditional ratings, it does not take into account any external support factors.

[18] We propose a plausible explanation that could help us understand better the weaknesses of the accounting model compared with the specifications including credit ratings. Specifically, the accounting standards are different from one European country to another, thus decreasing the degree of comparability of our proxies for bank risk and

Reserve, *Bad Loans*, and the corresponding interactive variables) exhibit in most cases significant coefficients (except for the FE specification).[19] The loan loss reserve is favorably perceived by investors as a supplementary cushion likely to absorb future expected losses on the credit portfolio for high-leveraged banks only. The effect is once again significantly stronger at the right tail of the distribution (see also Figure 4). The sign of *BadLoans* is negative, contradicting at first sight the rational pricing hypothesis. However, when this variable interacts with the financial leverage, the influence becomes positive and significant. This result suggests that for under-capitalized banks, a higher non performing loans ratio implies relatively larger spreads, in accordance with the conventional wisdom. The null hypothesis of homogenous coefficients at the tails (5^{th} and 95^{th} quantiles) is rejected at the 10% confidence level (for a visual inspection, also see Figure 4).

{Table 7 about here}

{Figure 4 about here}

To sum up, the empirical results presented in this section show the relevance of going beyond the standard conditional expectation model to study the quality of private monitoring in banking. The results indicate that the sensitivity of bond prices to various risk proxies (traditional and financial strength ratings and some fundamental credit risk measures computed from banks' balance-sheets) vary *considerably* along the conditional distribution of spread, in terms of statistical significance, economic magnitude, and goodness-of-fit measure. Importantly, our QR estimations reveal that the spread-risk relationship is stronger and more significant at the right tail of the conditional distribution of credit spread.

6. Conclusion

To draw inferences about the risk sensitivity of market prices and the quality of private monitoring in banking, most of the previous empirical studies have employed conventional least squares (OLS) regression methods. While the conditional expectations model can address the question "*do bond markets*

performance. The heterogeneity of accounting definitions is more severe in the case of non performing loans, loan loss reserves, and charge offs (also see Sironi, 2003, and Pop, 2006).

[19] The heterogeneity specification test (pooled *vs*. FE model) described in Hsiao (2003) indicates that the pooled specification is preferred to FE specification.

correctly price the risk profile for the 'average' bank?", it cannot answer an equally important question: "*do debt markets price the risk differently for banks in the upper tail of the spread distribution than for banks in the lower tail of the same distribution?*". As one of the main objectives of supervision is to correctly identify the worst 5 or 10% of banks, the answer to the second question is highly relevant from a public policy perspective. Indeed, it is important to draw appropriate inferences about the risk sensitivity of credit spreads at the right tail of the spread distribution.

The present paper proposes a different empirical approach based on quantile regressions and reveal that the effect of various risk proxies on the conditional mean of the credit spread variable are not fully informative of the magnitude of these effects at the right tail of the spread distribution. The QR framework allows us to provide a more comprehensive picture of the risk sensitivity of credit spreads by estimating a set of different conditional quantile functions. On the whole, our results confirm that secondary market prices are sensitive to the financial conditions and risk profiles of bank issuers, as reflected in traditional credit ratings and especially Moody's Bank Financial Strength and Fitch–IBCA Individual ratings, which are specific to financial firms. However, the relation between the spreads and accounting measures of bank risk and performance is weaker, in particular because of the heterogeneity of the accounting standards applied in various European countries. Going beyond the conventional OLS regression methods, the results from the QRs reveal that the link between market prices and risk proxies varies considerably along the conditional distribution of spread, both in terms of statistical significance and economic magnitude. More importantly, the spread-risk relationship is stronger and more significant at the right tail of the conditional distribution of credit spread. These findings suggest that the market is, in some sense, tougher with "high-risk" banks, a novel result that may not be captured using standard conditional mean-focused estimations commonly used in the literature.

The QR framework and the preliminary results reported in this paper are particularly relevant to the current debate around the *contingent capital proposals*; that is, proposals to require systemically important financial institutions to issue debt securities, which automatically converts to common equity when a predefined idiosyncratic trigger is reached during a systemic crisis (Flannery, 2005, 2009ab; Hart and Zingales, 2009; Squam Lake Working Group on Financial Regulation, 2009; Wall, 2010). Some of the proponents of contingent capital advocate for a market-based conversion trigger (e.g. equity prices, CDS or SND spreads) on the grounds that the accounting measures are inherently backward-looking and fail to reflect in a timely manner the true financial conditions of large and complex banking organizations.[20] Yet, the empirical evidence is very scarce, if not non-existent, on the ability of market-based indicators to send early-warning signals during systemic crises. The present study suggests a way to fill this important gap in the literature and shows the relevance of investigating the quality of the informational content of debt security prices in the right tail of the spread distribution. Indeed, the financial institutions that are the most likely to convert their contingent capital to common equity during a stressful period for the banking industry are, most probably, those firms located in the upper tail of the spread distribution. [21]

[20] Flannery (2009a) notes in this respect: "*contingent capital driven by a book-valued trigger is virtually worthless.*" In the same vein, Eisenbeis (2009) contends that "*it is critical that the trigger not be a matter of regulatory discretion, and it should be market-based*."

[21] In the present paper, we do not examine the design of the automatic conversion mechanism of contingent capital notes based on debt market prices or spreads. To reduce the incidence of pricing errors in various bank securities markets (equity, debt, CDS and so on), it might be an interested idea to construct an idiosyncratic weighted composite trigger based on equity prices, SND/CDS spreads and other market signals. This idea is left for future work.

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Appendix 1. Least squares polynomial method of best fit calculations for benchmark yield curves

This appendix contains the calculations for the least squares polynomial method of best fit used to plot benchmark yield curves stored in *Datastream*. The formulae describe the mathematical derivation of a polynomial equation as best fit to a series of data-points expressed as co-ordinates (X_i, Y_i), $i = 1, \ldots, n$.

The equation of the curve is:

$Y = a + bX + cX^2 + dX^3 + \varepsilon$

To fit a polynomial curve to the points, the standard method of least squares curve fitting is used. In this manner, the differences between the observed values of X and Y and the curve are minimized. Using this method, the values that determine the shape of the curve (a, b, c, and d) are found by solving the following linear simultaneous equations:

$$\sum_{i=1}^{n} Y_i = na + b\sum_{i=1}^{n} X_i + c\sum_{i=1}^{n} X_i^2 + d\sum_{i=1}^{n} X_i^3$$

$$\sum_{i=1}^{n} Y_i X_i = a\sum_{i=1}^{n} X_i + b\sum_{i=1}^{n} X_i^2 + c\sum_{i=1}^{n} X_i^3 + d\sum_{i=1}^{n} X_i^4$$

$$\sum_{i=1}^{n} Y_i X_i^2 = a\sum_{i=1}^{n} X_i^2 + b\sum_{i=1}^{n} X_i^3 + c\sum_{i=1}^{n} X_i^4 + d\sum_{i=1}^{n} X_i^5$$

$$\sum_{i=1}^{n} Y_i X_i^3 = a\sum_{i=1}^{n} X_i^3 + b\sum_{i=1}^{n} X_i^4 + c\sum_{i=1}^{n} X_i^5 + d\sum_{i=1}^{n} X_i^6$$

where Y_i = observation of the "redemption yield" for a treasury security in list;
X_i = observation of the "life" for a corresponding treasury security in list;
n = number of treasury securities in list.

These equations are solved using matrix reduction techniques to provide values for a, b, c, and d. The situation above describes the derivation of the equation of a curve in the 3rd power of X. For each market, two types of benchmark yield curve are calculated: to the power of 3 and to the power of 5. A better fit is achieved as the squared multiple correlation coefficient (R^2) approaches 1.

Notes:

1° Yield curves of the French government contain 3-month money market rates in order to stabilize the short end of the yield curve.

2° Values for spreads do not include bonds that are perpetual or whose life exceeds the maturity value range for the market (i.e. [0.8–12] for Germany, Italy, the Netherlands, Switzerland, and [0.8–32] for the US, France, the UK). To do so would produce meaningless spread values through extrapolation.

Appendix 2. Ratings scales

a) Traditional credit ratings

Cardinal value	1	2	3	4	5	6	7	8	9	10	11	12	13	14
S&P	AAA	AA+	AA	AA–	A+	A	A–	BBB+	BBB	BBB–	BB+	BB	BB–	B+
Moody’s	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1
Fitch	AAA	AA+	AA	AA–	A+	A	A–	BBB+	BBB	BBB–	BB+	BB	BB–	B+

b) Financial strength ratings

Cardinal value	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MBFS	A	A–	B+	B	B–	C+	C	C–	D+	D	D–	E+	E	E–
Cardinal value	1	2.5		4	5.5		7	8.5		10	11.5		13	
FII	A	A/B		B	B/C		C	C/D		D	D/E		E	_

Table 1
SPREAD and Ratings -- Distribution by Year

	SPREAD[a] (%)			SP-M-FI[b]			MBFS-FII[c]		
Year	*N*	Mean	Std. dev.	*N*	Mean	Std. dev.	*N*	Mean	Std. dev.
1995	50	0.544	0.352	47	3.68	1.83	33	4.27	2.14
1996	56	0.641	0.524	48	3.70	1.90	39	4.15	2.10
1997	65	0.745	0.724	52	3.71	1.86	41	4.34	2.12
1998	70	1.032	0.976	53	3.68	1.69	48	4.78	2.19
1999	70	0.903	0.832	55	3.74	1.60	51	4.85	2.05
2000	70	0.994	0.751	58	3.73	1.52	54	4.85	1.97
2001	70	0.938	0.804	63	3.97	1.57	55	4.65	1.71
2002	70	1.020	1.124	63	4.15	1.65	56	4.84	1.85
1995--2002	521	0.871	0.825	439	3.81	1.69	377	4.63	2.00

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security calculated by substituting the value for the life of the bond into the cubic equation that describes the benchmark yield curve of corresponding sovereign.

[b] SP-M-FI is calculated as the mean of long term issuer ratings assigned by Moody's, Standard and Poor's and Fitch-IBCA, converted to cardinal values as shown in Appendix 2a. A higher credit quality corresponds to a lower cardinal number.

[c] MBFS-FII is the mean of financial strength ratings assigned by Moody's/Fitch-IBCA, cardinalized as shown in Appendix 2b.

Table 2

Sample Descriptive Statistics -- Distribution by Country[a]

Country	No. of banks	SPREAD (%)		Ratings		AISD	Total assets	ROAA	Leverage	Net loans	LLR	Bad loans
		Mean	Std. dev.	SP-M-FI	MBFS-FII	(m. US$)	(bn. US$)	(%)		(%)	(%)	(%)
Austria	4	0.59	0.34	3.96	6.35	56.77	57.99	0.33	26.30	56.11	4.29	3.74
Belgium	2	0.67	0.34	4.09	4.25	64.78	229.00	0.55	26.88	40.64	1.88	2.83
Denmark	1	0.24	0.11	NA	NA	1,408.69	5.75	0.16	18.30	33.26	1.29	1.54
France	13	0.75	0.48	4.61	5.53	403.40	191.00	0.56	25.91	50.04	4.31	6.12
Germany	11	0.59	0.47	2.71	5.26	213.54	260.00	0.21	35.58	49.67	2.37	2.79
Ireland	1	0.99	0.31	4.58	4.00	158.38	56.36	1.25	16.22	66.99	1.07	1.73
Italy	5	1.76	2.01	5.79	6.77	224.26	99.51	0.44	17.81	59.06	3.76	8.21
Luxembourg	3	0.87	0.60	3.67	3.30	29.16	31.18	0.62	29.25	17.55	NA	NA
Netherlands	7	0.49	0.27	2.78	3.26	239.48	222.00	0.64	20.38	62.31	1.26	1.63
Norway	1	1.75	1.07	6.00	NA	106.44	36.06	0.91	15.75	71.06	2.47	1.62
Spain	4	1.68	1.03	4.53	4.18	200.00	213.00	0.76	15.91	48.78	3.00	2.78
Sweden	2	2.09	1.53	5.03	5.22	150.00	101.00	0.63	24.27	56.99	1.04	2.32
Switzerland	6	0.70	0.44	2.87	2.81	224.14	211.00	0.42	19.10	55.43	3.95	4.47
UK	10	1.00	0.46	3.41	3.29	330.56	188.00	0.81	21.08	65.19	1.27	2.21
Total	70	0.87	0.82	3.81	4.63	260.17	179.00	0.53	24.35	53.58	2.90	3.99

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security obtained by substituting the bank debt maturity in the cubic equation that describes the benchmark yield curve of corresponding sovereign. *SP-M-FI* is the mean of traditional credit ratings (Standard and Poor's, Moody's and Fitch-IBCA) cardinalized as shown in Appendix 2a. *MBFS-FII* is the mean of financial strength (Moody's) and individual (Fitch-IBCA) bank specific ratings (cardinalized values). *AISD* is the US dollar-equivalent amount outstanding. *ROAA* is the ratio of annual net income to the average of the preceding and current year-end total assets. *Leverage* is the ratio of total (book) liabilities to the book value of equity. *Net loans* -- the ratio of net loans to total assets. *LLR* is the reserve for loan losses expressed as percentage of total loans. *Bad loans* -- the ratio of total problem loans to total (net) loans. *NA* = data non available

Table 3
SPREAD -- Distribution by Rating Classes[a]

	N	Mean	Std. dev.	Minimum	Maximum	Quartiles		
						Lower	Median	Upper
Panel A: Traditional ratings (S&P, Moody's, and Fitch-IBCA)								
AAA/Aaa	51	0.34	0.28	–0.34	1.46	0.23	0.30	0.45
AA/Aa	251	0.84	0.57	–0.06	4.94	0.47	0.72	1.10
A	112	1.22	1.31	–0.88	7.78	0.46	0.90	1.27
BBB/Baa	3	1.26	0.53	0.66	1.68	0.66	1.43	1.68
NR	104	0.83	0.68	–1.01	3.20	0.39	0.59	1.14
Total	521	0.87	0.82	–1.01	7.78	0.40	0.68	1.10
Panel B: Financial strength ratings (Moody's and Fitch-IBCA)								
A	43	0.50	0.41	–0.34	1.73	0.23	0.48	0.71
B	212	0.92	0.70	–0.06	5.12	0.48	0.77	1.13
C	87	1.09	1.39	–0.33	7.78	0.39	0.56	1.16
D	20	0.82	0.47	–0.02	1.94	0.47	0.80	1.03
NR	159	0.79	0.62	–1.01	3.20	0.37	0.64	1.10
Total	521	0.87	0.82	–1.01	7.78	0.40	0.68	1.10

[a] SPREAD is the difference between the bond yield to maturity and the yield of a corresponding currency Treasury security obtained by substituting the value for the life of the bond into the cubic equation describing the benchmark yield curve of corresponding sovereign. The traditional ratings are represented by the mean of long term issuer ratings assigned by Moody's, Standard and Poor's, and Fitch-IBCA, cardinalized as shown in Appendix 2a. The financial strength ratings are represented by the mean of the bank specific ratings assigned by Moody's and Fitch-IBCA (cardinalized values). The AA class includes the AA+, AA, AA– sub-classes, etc. *NR* = no rating available

Table 4
Description of the Main Explanatory Variables

Variable	Definition	Expected sign
ROAA	Return on average assets, calculated by dividing the annual net income to the average of the preceding and current year-end total assets	+/–
Capital ratio	Total capital adequacy ratio calculated according to Basel I	–
Leverage	Financial leverage, calculated as the ratio of total (book) liabilities to the book value of equity	+
NetLoans	Ratio of net loans to total assets, a measure of the opaqueness of banking firm's assets	+
Liquidity	Liquidity ratio, indicating what percentage of customer and short term funds could be met if they are suddenly withdrawn	–
Loan Loss Res	Ratio of loan loss reserves to total (gross) loans, indicating how much of the total credit portfolio has been provided for but not charged off	+/–
BadLoans	Ratio of total problem loans to total (net) loans, a proxy for the quality of the loan portfolio	+
ROAA*Lev	Product of ROAA and Leverage	–
LLR*Lev	Product of Loan Loss Res (LLR) and Leverage	–
BadLoans*Lev	Product of BadLoans and Leverage	–
ln(AISD)	Log of the outstanding amount of the issue, expressed in thousand US$, a proxy for liquidity effects on spreads	–
Maturity	Remaining maturity, expressed in years	+
α_t, t={95,…,02}	"Year" dummies, quantifying the inter-temporal variations in bond market conditions	+
France, Germany, Sweden, Switzerland, UK	"Country" dummy variables, capturing both differences in macroeconomic conditions and differences in safety nets across countries	+/–
Subordinated	Takes the value of 1 if the (unsecured) debt has a subordinated status and 0 otherwise	+
Split	Dummy variable equal to 1 if the bank issuer received a rating from Moody's that is different from the rating it received from S&P. According to Morgan (2002), split ratings are a sign that the bank's financial condition is opaque to investors	+
Support	"External support" dummy variable, taking the value of 1 if the issuer is either a public-sector bank or a bank that benefits from explicit/implicit governmental guarantees and 0 otherwise. The presence of explicit/implicit guarantees is confirmed by a Fitch–IBCA Support rating equal to 1	–

Table 5

OLS and QR Results: Traditional Ratings[a]

Independent	OLS[b]		Quantile regressions[c]							*F*-test[d]		
Variables	*Pooled*	*FE*	*Q .05*	*Q .10*	*Q .25*	*Q .50*	*Q .75*	*Q .90*	*Q .95*	*Q.25=Q.75*	*Q.25=Q.50=Q.75*	*Q.05=Q.95*
Const	3.554***	0.121	0.079	–0.414	0.494	0.427	1.019	4.225**	5.821***			
	(3.376)	(0.703)	(0.187)	(–1.014)	(1.166)	(0.925)	(1.379)	(2.020)	(3.023)			
SP-M-FI	0.064***	0.193***	0.027	0.032*	0.033**	0.053***	0.100***	0.126**	0.210***	7.52***	3.76**	5.12**
	(3.354)	(4.196)	(1.193)	(1.664)	(2.112)	(3.584)	(4.313)	(2.284)	(2.639)			
Split	0.204***	0.102	0.061	0.084*	0.073	0.133**	0.210***	0.185	0.218	2.96*	1.48	0.45
	(2.920)	(1.307)	(1.070)	(1.694)	(1.505)	(2.283)	(2.712)	(1.168)	(1.023)			
ln(AISD)	–0.297***		–0.062*	–0.009	–0.054*	–0.048	–0.088	–0.299*	–0.390***	0.41	0.22	4.71**
	(–3.626)		(–1.728)	(–0.306)	(–1.783)	(–1.438)	(–1.577)	(–1.886)	(–2.601)			
Maturity	0.014*		0.028***	0.031***	0.032***	0.030***	0.032***	0.017	0.007	0.00	0.00	1.97
	(1.748)		(4.143)	(4.671)	(5.278)	(4.312)	(3.744)	(1.298)	(0.469)			
Subordinated	0.100		0.475***	0.392***	0.270***	0.235***	0.099	–0.022	–0.121	5.31**	2.66*	6.02**
	(1.113)		(6.971)	(5.609)	(4.529)	(3.751)	(1.432)	(–0.115)	(–0.510)			
Ctry dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	417	417	417	417	417	417	417	417	417			
Adj/Pseudo R2	0.340	0.672	0.233	0.178	0.203	0.229	0.216	0.274	0.402			

[a] Dependent variable is SPREAD (%) calculated as difference between actual yields on the bank debt and the constructed yield on a corresponding treasury security with the same maturity. Explanatory variables are defined as follows: *SP-M-FI* -- the average traditional credit rating assigned by S&P, Moody's, and Fitch, converted to cardinal values; *Split* -- dummy variable that takes the value of 1 if Moody's ≠ S&P; *ln(AISD)* -- the log of the US dollar-equivalent amount of the issue (in thousand); *Maturity* -- the remaining maturity expressed in years; *Subordinated* equals 1 if the bond is subordinated.

[b] OLS regressions: estimated standard errors are computed using White's method; heteroskedasticity-consistent *t*-statistics are reported in parentheses below each OLS coefficient estimate

[c] Quantile regressions: *t*-statistics reported in parentheses below each QR coefficient estimate are based on bootstrap standard errors computed using 1,000 replications; the reported pseudo-R2 is calculated as 1 – [sum of the weighted deviations about estimated quantile / sum of weighted deviations about raw quantile]

[d] Wald test for the equality of QR coefficients across various quantiles

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

Table 6

OLS and QR Results: Financial Strength Ratings and Governmental Guaranties[a]

Independent	OLS[b]		Quantile regressions[c]							*F*-test[d]		
Variables	*Pooled*	*FE*	*Q .05*	*Q .10*	*Q .25*	*Q .50*	*Q .75*	*Q .90*	*Q .95*	*Q.25=Q.75*	*Q.25=Q.50=Q.75*	*Q.05=Q.95*
Const	4.434***	0.363**	0.069	0.021	0.547	0.889*	1.802	7.087***	8.029***			
	(3.982)	(2.120)	(0.158)	(0.048)	(1.096)	(1.438)	(1.400)	(3.813)	(4.321)			
MBFS-FII	0.047***	0.134***	0.027**	0.040***	0.030**	0.038**	0.061***	0.127***	0.174***	2.44*	1.22	0.13
	(2.809)	(4.468)	(2.060)	(3.182)	(2.434)	(2.759)	(3.120)	(3.063)	(3.509)			
Split	0.262***	0.105	0.016*	0.064	0.071	0.145**	0.278***	0.329**	0.306	4.22**	2.30*	0.09
	(3.058)	(0.962)	(0.243)	(1.114)	(1.258)	(2.258)	(3.294)	(2.177)	(1.484)			
ln(AISD)	–0.354***		–0.067**	–0.053	–0.068*	–0.081**	–0.148*	–0.540***	–0.563***	0.03	0.02	9.65***
	(–4.063)		(–1.854)	(–1.530)	(–1.897)	(–2.337)	(–1.654)	(–3.848)	(–3.804)			
Maturity	0.019*		0.025***	0.029***	0.034***	0.032***	0.033***	0.024	0.013	0.02	0.07	0.13
	(2.185)		(3.931)	(4.483)	(5.279)	(4.255)	(3.062)	(1.395)	(0.688)			
Subordinated	0.055		0.458***	0.398***	0.281***	0.215***	0.140	–0.180	–0.106	0.00	0.57	0.46
	(0.613)		(6.787)	(5.449)	(4.040)	(2.933)	(1.428)	(–1.067)	(–0.506)			
Support	–0.213***	–0.366*	0.152**	0.085	–0.011	–0.089	–0.185***	–0.261**	–0.239	0.00	6.13***	0.10
	(–3.185)	(–1.760)	(2.635)	(1.356)	(–0.203)	(–1.768)	(–2.583)	(–1.993)	(–1.352)			
Ctry dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	362	362	362	362	362	362	362	362	362			
Adj/Pseudo R2	0.326	0.685	0.274	0.210	0.226	0.249	0.249	0.334	0.453			

[a] Dependent variable is SPREAD (%) calculated as difference between actual yields on the bank debt and the constructed yield on a corresponding treasury security with the same maturity. Explanatory variables are defined as follows: *MBFS-FII* -- the average financial strength rating (cardinalized value); *Split* -- dummy variable that takes the value of 1 if Moody's ≠ S&P; *ln(AISD)* -- the log of the US dollar-equivalent amount of the issue (in thousand); *Maturity* -- the remaining maturity expressed in years; *Subordinated* equals 1 if the bond is subordinated; *Support* equals 1 if the issuing bank is a "public-sector" one (i.e. either government-owned or having a Fitch-IBCA Support rating equal to 1).

[b] OLS regressions: estimated standard errors are computed using White's method; heteroskedasticity-consistent *t*-statistics are reported in parentheses below each OLS coefficient estimate

[c] Quantile regressions: *t*-statistics reported in parentheses below each QR coefficient estimate are based on bootstrap standard errors computed using 1,000 replications; the reported pseudo-R2 is calculated as 1 – [sum of the weighted deviations about estimated quantile / sum of weighted deviations about raw quantile]

[d] Wald-test for the equality of QR coefficients across various quantiles

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

Table 7
OLS and QR Results: Accounting Variables[a]

Independent	OLS[b]		Quantile regressions[c]							*F*-test[d]		
Variables	*Pooled*	*FE*	*Q .05*	*Q .10*	*Q .25*	*Q .50*	*Q .75*	*Q .90*	*Q .95*	*Q.25=Q.75*	*Q.25=Q.50=Q.75*	*Q.05=Q.95*
Constant	6.996***	0.630	1.518	2.014*	2.183**	3.027**	7.657***	8.330***	9.287***			
	(6.064)	(1.221)	(1.427)	(1.955)	(2.154)	(1.922)	(3.877)	(3.914)	(4.444)			
ln(AISD)	–0.451***		–0.100	–0.157**	–0.150**	–0.186*	–0.472***	–0.551***	–0.685***	7.90***	4.53**	13.12***
	(–5.597)		(–1.441)	(–2.397)	(–2.413)	(–1.788)	(–3.602)	(–4.148)	(–4.740)			
Maturity	0.020		0.057***	0.042**	0.026*	0.036*	0.034	0.026	0.035	0.10	0.18	0.32
	(1.279)		(2.787)	(2.107)	(1.757)	(1.883)	(1.428)	(0.810)	(1.086)			
Subordinated	0.200*		0.374**	0.378**	0.256**	0.252*	0.232	0.432**	0.477**	0.02	0.01	0.15
	(1.807)		(2.394)	(2.737)	(2.133)	(1.949)	(1.532)	(2.254)	(2.172)			
Split	0.147	0.130	0.157	0.166*	0.168**	0.126	–0.048	–0.050	–0.272	1.85	0.94	3.49*
	(1.451)	(1.187)	(1.449)	(1.609)	(2.049)	(1.169)	(–0.306)	(–0.267)	(–1.230)			
Capital Ratio	–0.064**	0.015	–0.022	–0.020	–0.009	–0.019	–0.057	–0.058	–0.062	1.33	0.67	0.32
	(–2.511)	(0.563)	(–0.660)	(–0.691)	(–0.361)	(–0.616)	(–1.418)	(–1.064)	(–0.971)			
ROAA	0.625**	0.557	0.173	0.161	0.425	0.370	0.446	0.342	0.311	0.00	0.03	0.02
	(2.016)	(1.475)	(0.482)	(0.436)	(1.328)	(1.110)	(0.829)	(0.469)	(0.378)			
ROAA*Lev	–0.023*	–0.015	0.001	–0.001	–0.015	–0.016	–0.025	–0.028	–0.012	0.15	0.10	0.08
	(–1.675)	(–1.020)	(0.059)	(–0.083)	(–1.177)	(–0.975)	(–0.995)	(–0.774)	(–0.273)			
NetLoans	–0.001	0.007	–0.009*	–0.002	–0.000	–0.001	–0.007	–0.003	–0.001	0.61	0.34	0.50
	(–0.265)	(0.956)	(–1.666)	(–0.404)	(–0.096)	(–0.225)	(–0.796)	(–0.320)	(–0.078)			
Liquidity	0.008*	–0.005	0.001	0.004	0.003	0.004	0.007	0.008	0.021	0.27	0.14	1.98
	(1.721)	(–0.801)	(0.206)	(1.000)	(0.827)	(0.733)	(0.803)	(0.635)	(1.450)			
Loan Loss Res	0.488***	–0.111	0.388**	0.326*	0.401**	0.406***	0.406	0.878**	1.533***	0.00	0.00	5.19**
	(3.268)	(–0.566)	(2.058)	(1.784)	(2.617)	(2.613)	(1.602)	(2.224)	(3.220)			
LLR*Lev	–0.018***	0.003	–0.012*	–0.011*	–0.013**	–0.014**	–0.011	–0.026*	–0.048***	0.04	0.06	4.25**
	(–3.316)	(0.424)	(–1.857)	(–1.800)	(–2.464)	(–2.329)	(–1.077)	(–1.808)	(–2.803)			
Bad Loans	–0.434***	–0.060	–0.354***	–0.328***	–0.322***	–0.310***	–0.304*	–0.481*	–0.828***	0.01	0.01	2.15
	(–4.258)	(–0.415)	(–2.645)	(–2.563)	(–3.028)	(–3.026)	(–1.836)	(–1.798)	(–2.659)			
Bad Loans*Lev	0.014***	0.002	0.011**	0.010**	0.010***	0.010**	0.008	0.017	0.031**	0.13	0.07	2.63*
	(3.967)	(0.484)	(2.402)	(2.458)	(2.726)	(2.211)	(1.145)	(1.624)	(2.580)			
Support	–0.393***	–0.569***	–0.190	–0.222	–0.122	–0.195	–0.356*	–0.281	–0.530**	1.18	0.59	1.28
	(–3.235)	(–2.325)	(–1.304)	(–1.676)	(–1.157)	(–1.516)	(–1.628)	(–1.116)	(–2.020)			
Ctry dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	241	241	241	241	241	241	241	241	241			
Adj/Pseudo R2	0.406	0.680	0.419	0.302	0.266	0.257	0.313	0.465	0.581			

[a] Dependent variable is (end-of-January) SPREAD (%). *ln(AISD)* -- the log of the US dollar-equivalent amount of the issue (in thousand); *Maturity* -- the time to maturity (expressed in years); *Subordinated* equals 1 if the bond is subordinated; *Split* is a dummy variable that takes the value of 1 if Moody's ≠ S&P; *Capital Ratio* -- the total capital adequacy ratio under the Basle rules; *ROAA* -- the ratio of annual net income to the average of the preceding and current year-end total assets; *ROAA*Lev* -- the product of *ROAA* and financial leverage, measured as the ratio of total (book) liabilities to the book value of equity; *NetLoans* -- the ratio of net loans to total assets; *Liquidity* -- a deposit run off ratio; *LLR* -- the reserve for losses expressed as percentage of total loans; *LLR*Lev* -- the product of *LLR* and financial leverage; *BadLoans* -- the ratio of total problem loans to total (net) loans; *BadLoans*Lev* -- the product of *BadLoans* and financial leverage; *Support* equals 1 if the issuer is a "public" bank (i.e. either government-owned or having a Fitch-IBCA Support rating equal to 1).

[b] <u>OLS regressions:</u> estimated standard errors are computed using White's method; heteroskedasticity-consistent *t*-statistics are reported in parentheses below each OLS coefficient estimate

[c] <u>Quantile regressions:</u> *t*-statistics reported in parentheses below each QR coefficient estimate are based on bootstrap standard errors computed using 1,000 replications; the reported pseudo-R2 is calculated as 1 – [sum of the weighted deviations about estimated quantile / sum of weighted deviations about raw quantile]

[d] Wald-test for the equality of QR coefficients across various quantiles

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 1

Quantiles of the dependent variable: credit spread (%)

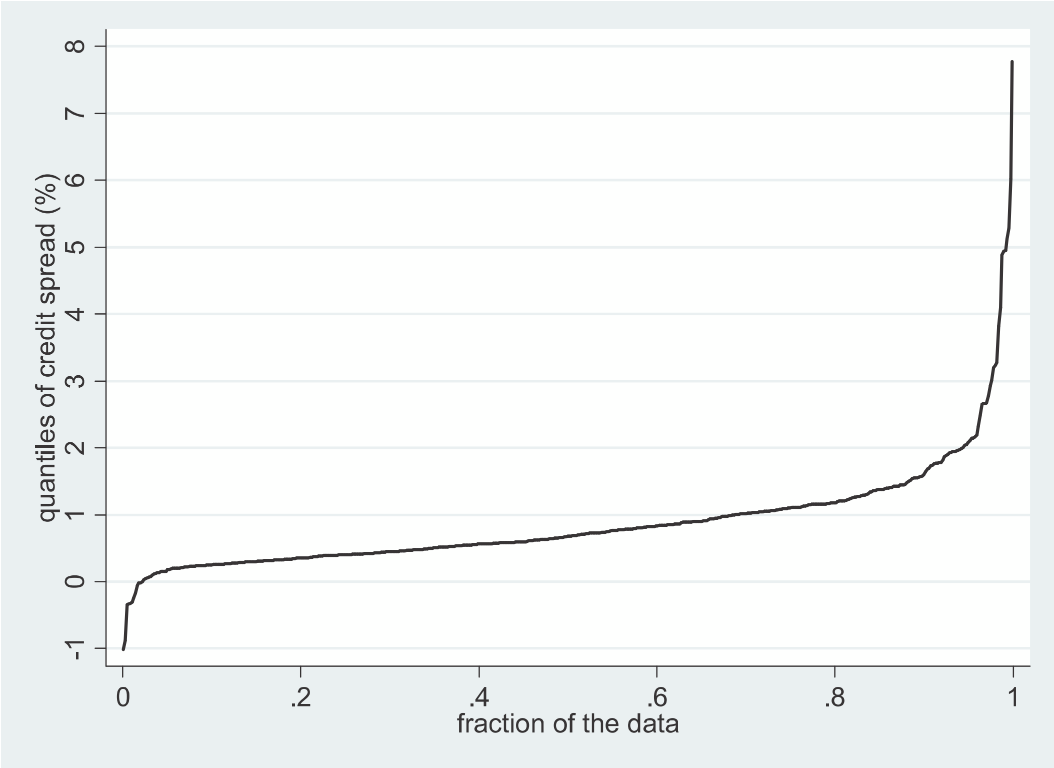


Figure 2

QR and OLS coefficients and 95% confidence bands: "traditional credit ratings"

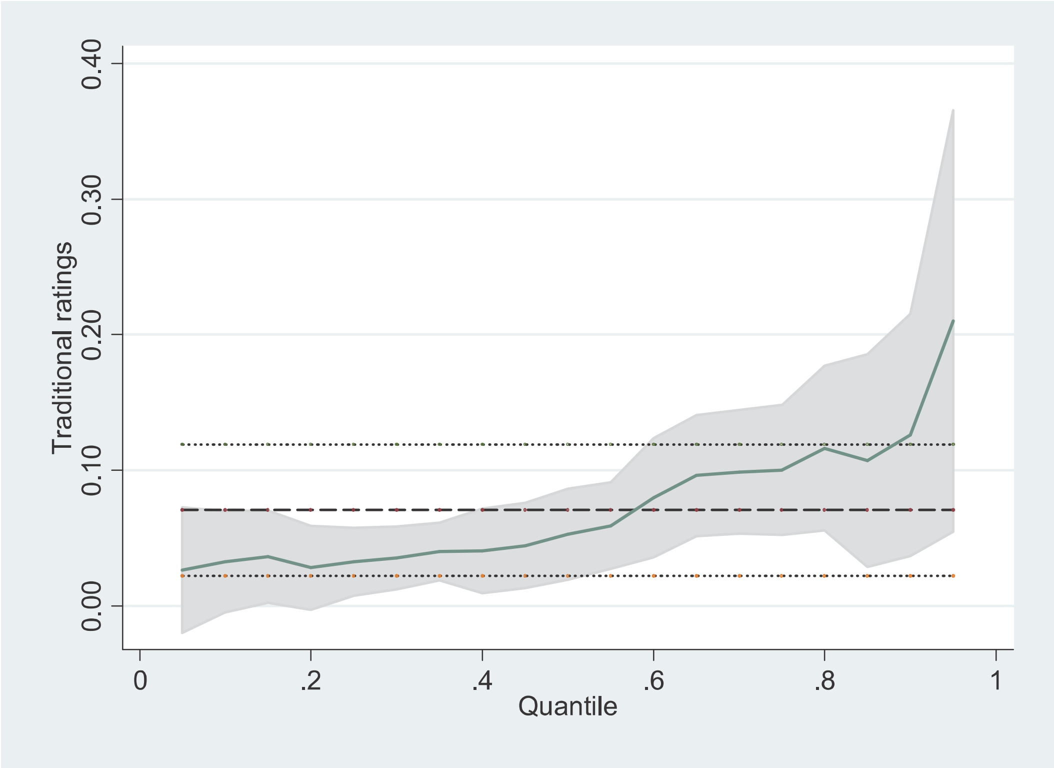


Figure 3

QR and OLS coefficients and 95% confidence bands: "financial strength ratings"

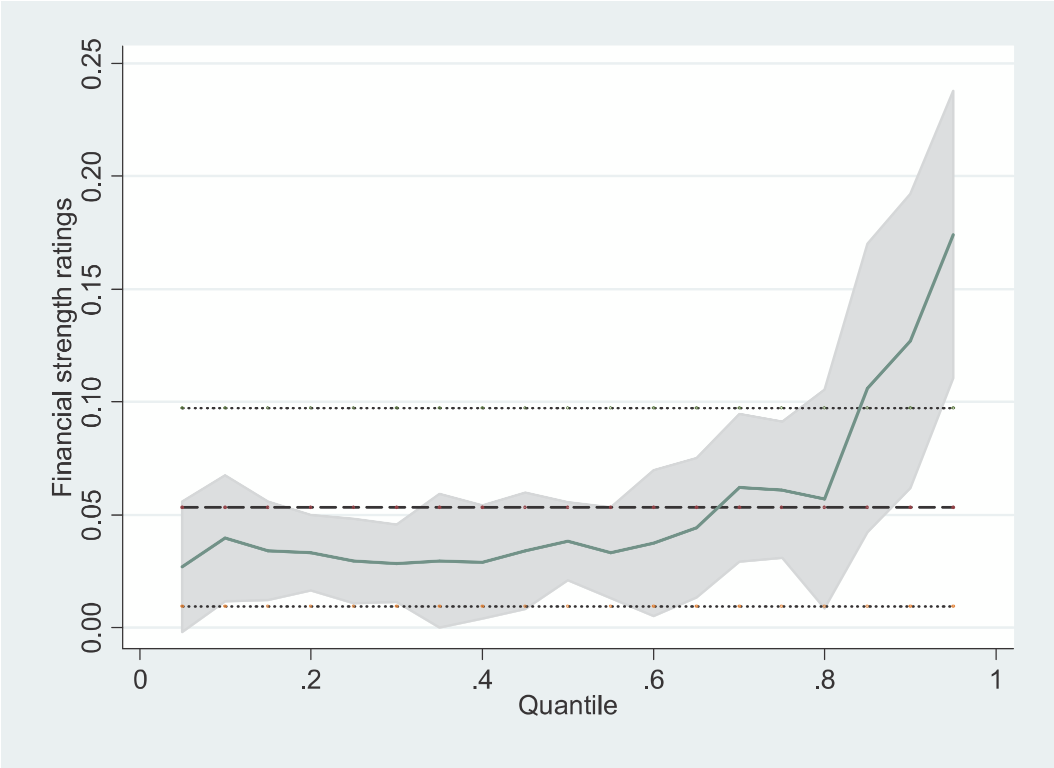
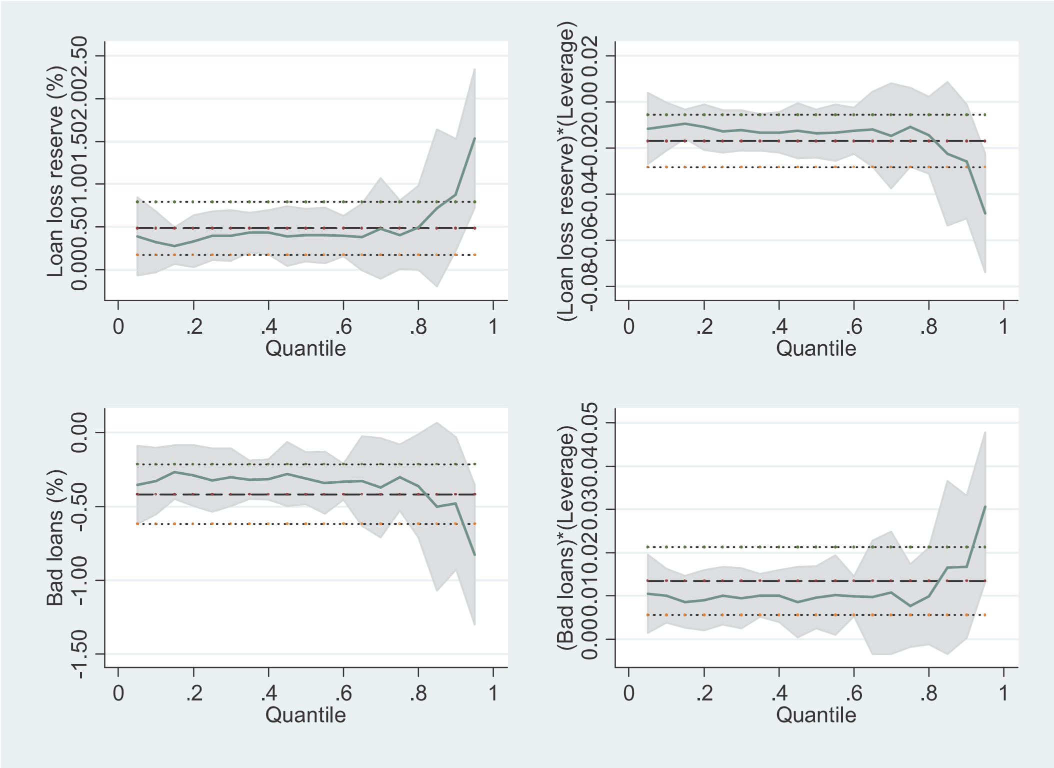


Figure 4
QR and OLS slope estimates and confidence bands: selected credit risk variables



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